# Project 16: Da Vinci Intelligent Surgical Assistance

# Seminar Presentation

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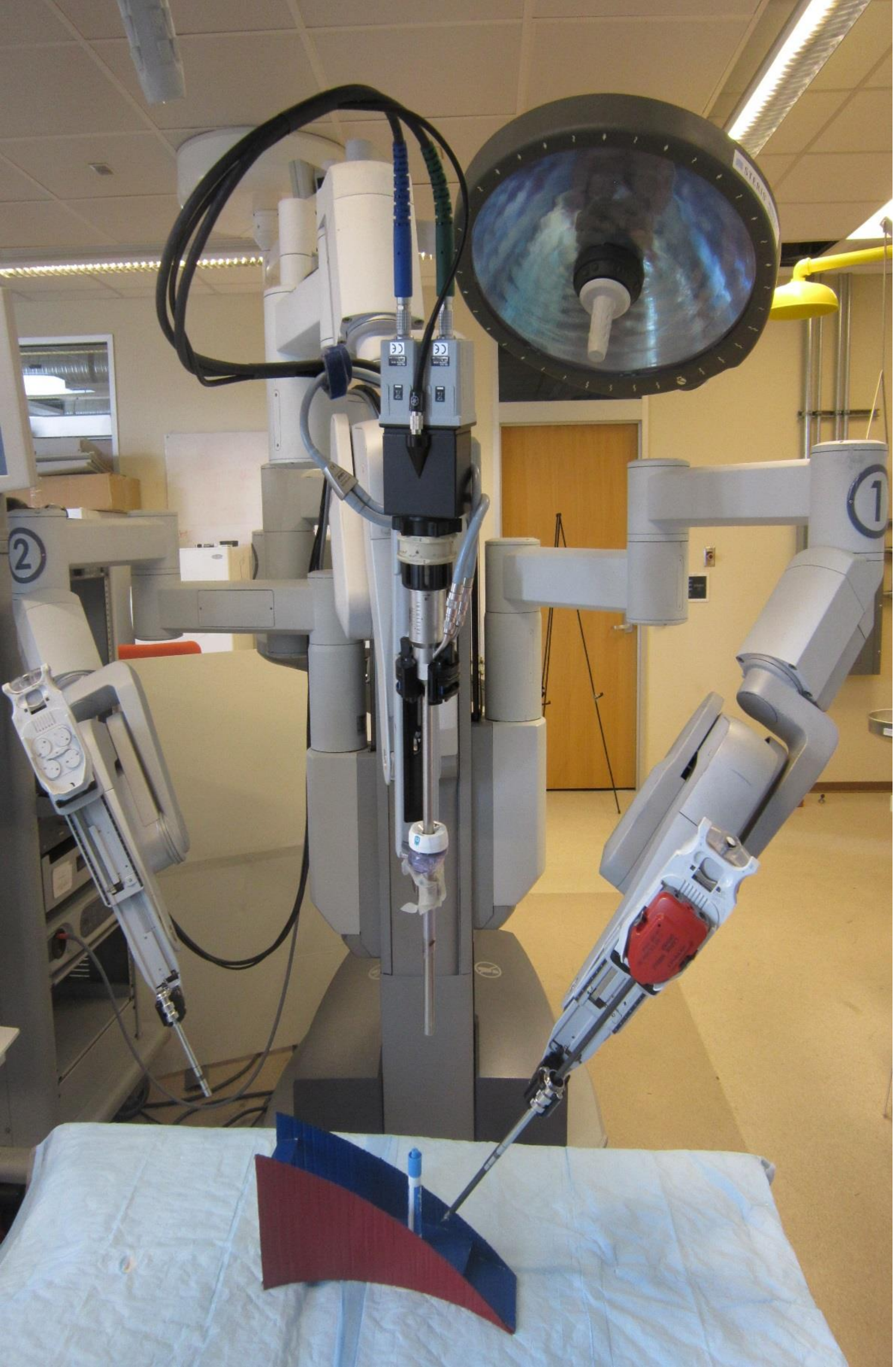
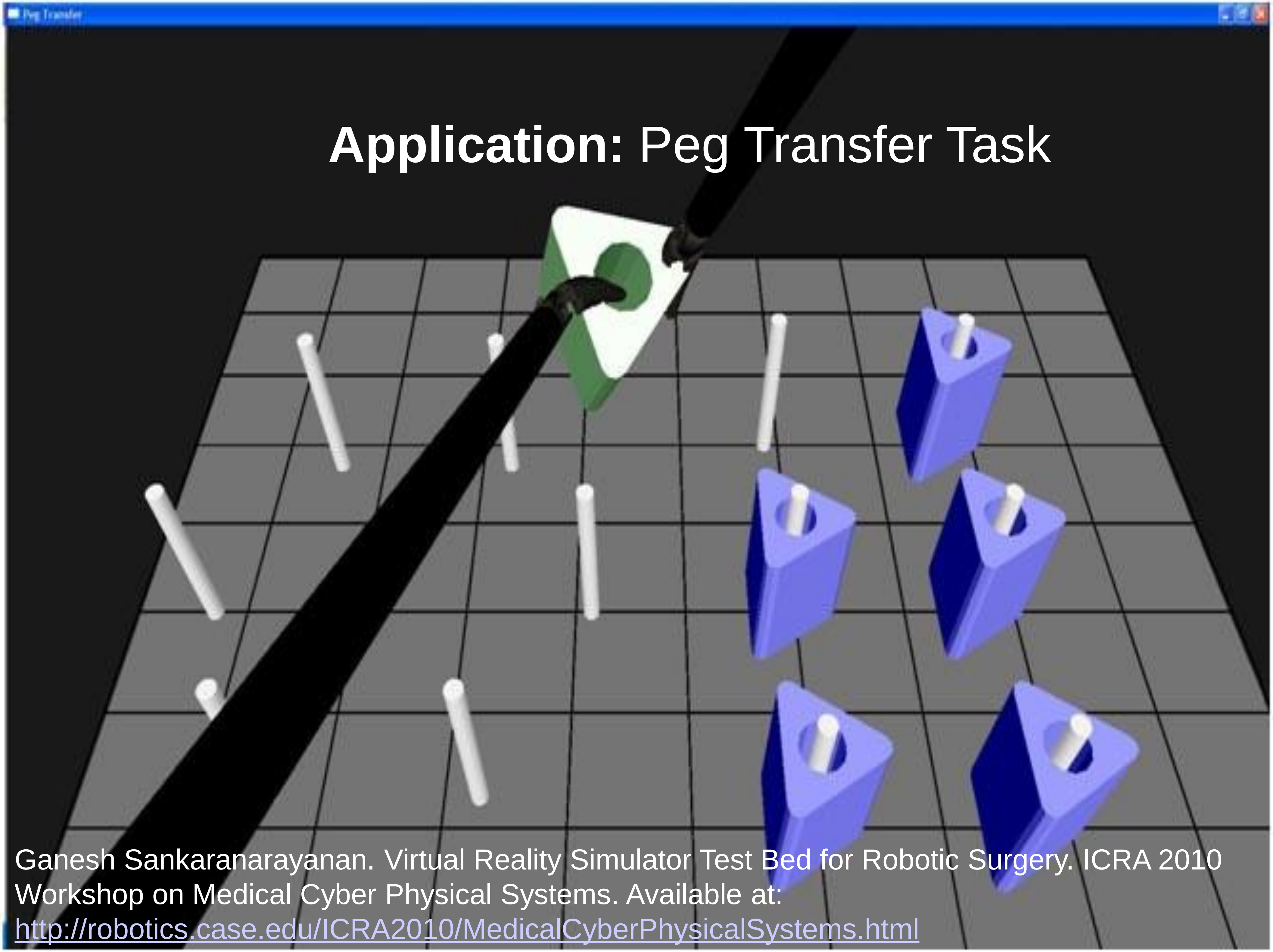


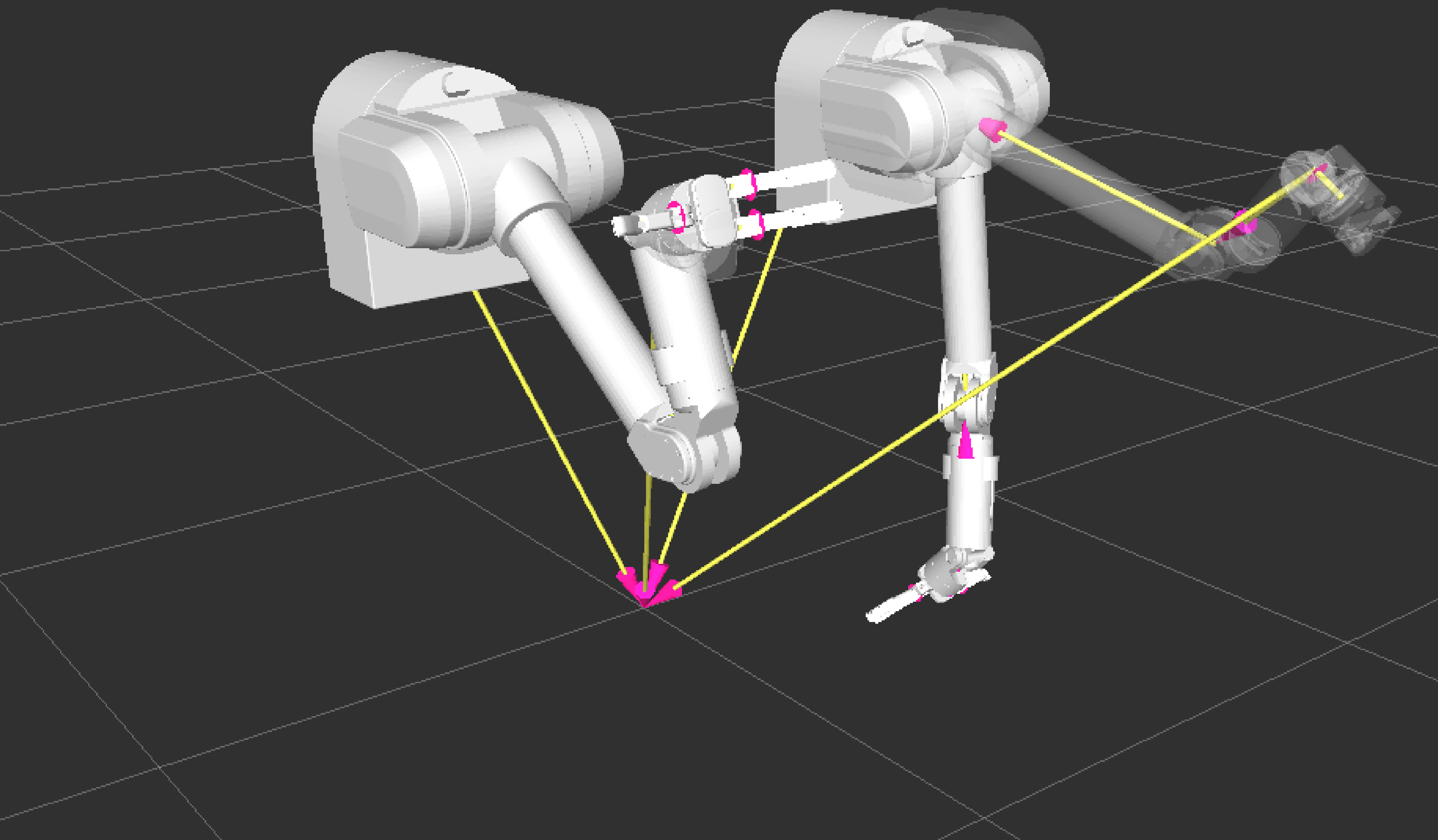

# Goals

- Learning from demonstration how to perform tasks (IOC)
- Collaborative execution of a simple pick and place task
- Collaborative execution of a robotic suturing task

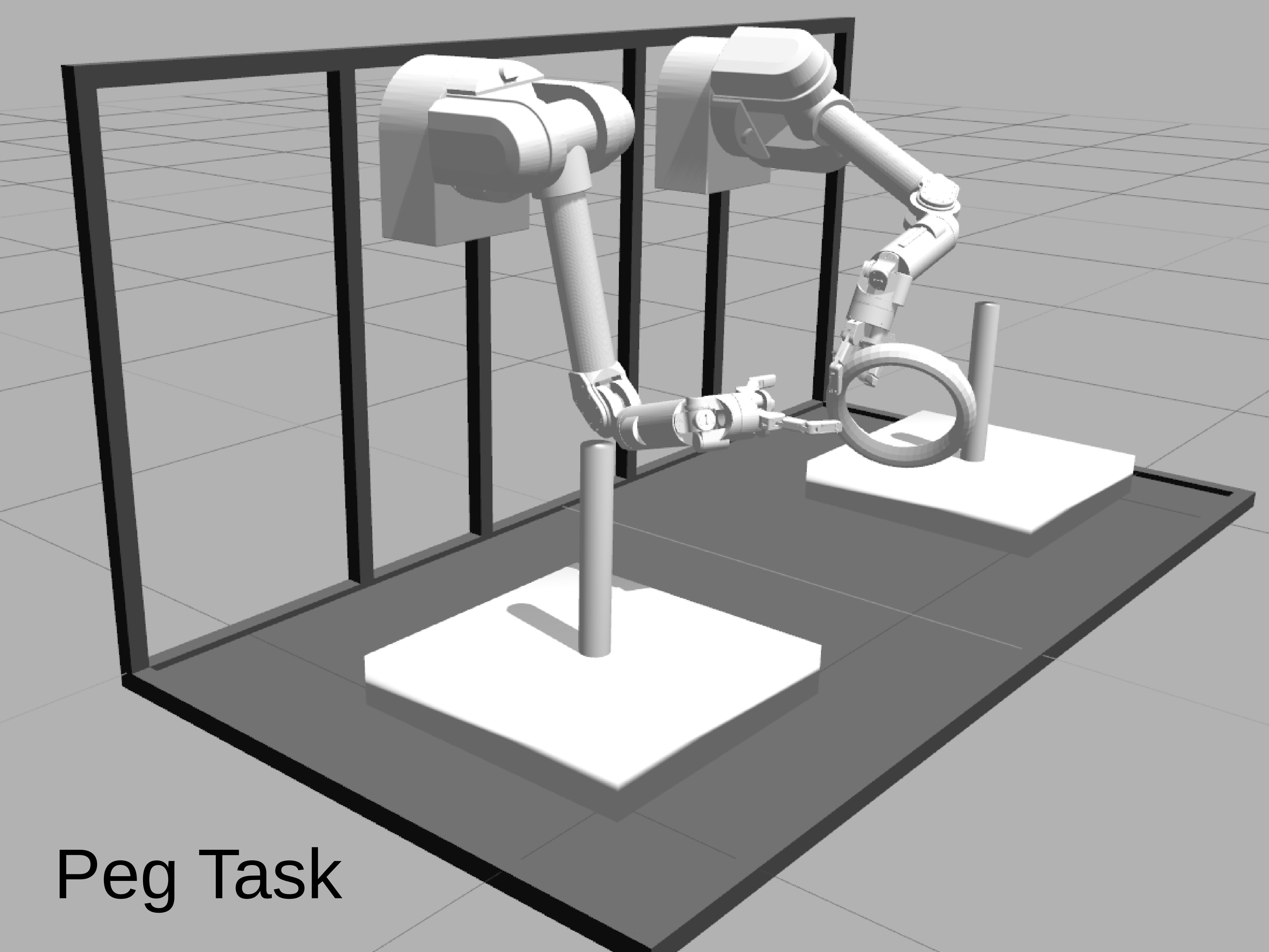
# **Application:** Peg Transfer Task

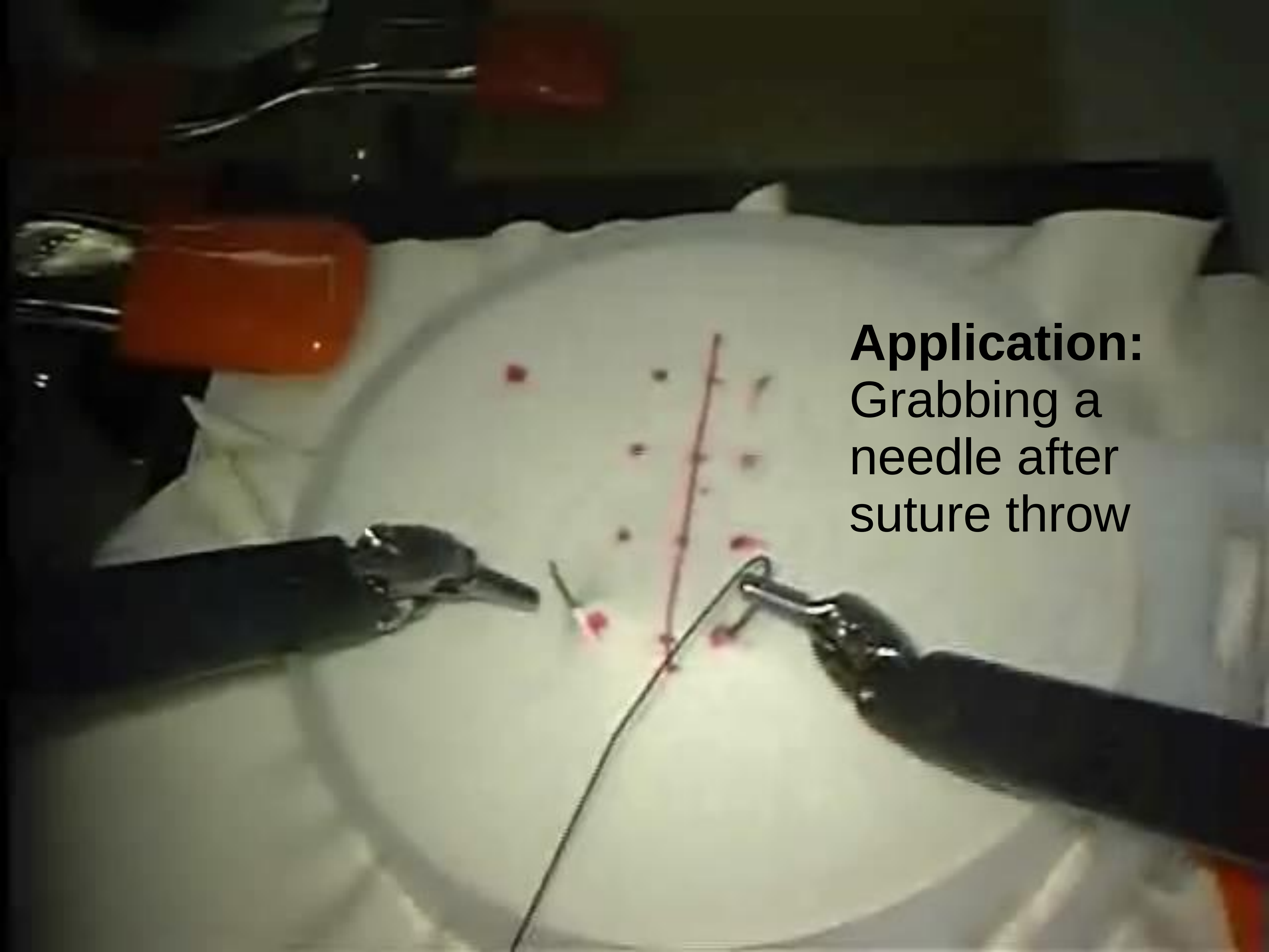



Ganesh Sankaranarayanan. Virtual Reality Simulator Test Bed for Robotic Surgery. ICRA 2010 Workshop on Medical Cyber Physical Systems. Available at: http://robotics.case.edu/ICRA2010/MedicalCyberPhysicalSystems.html



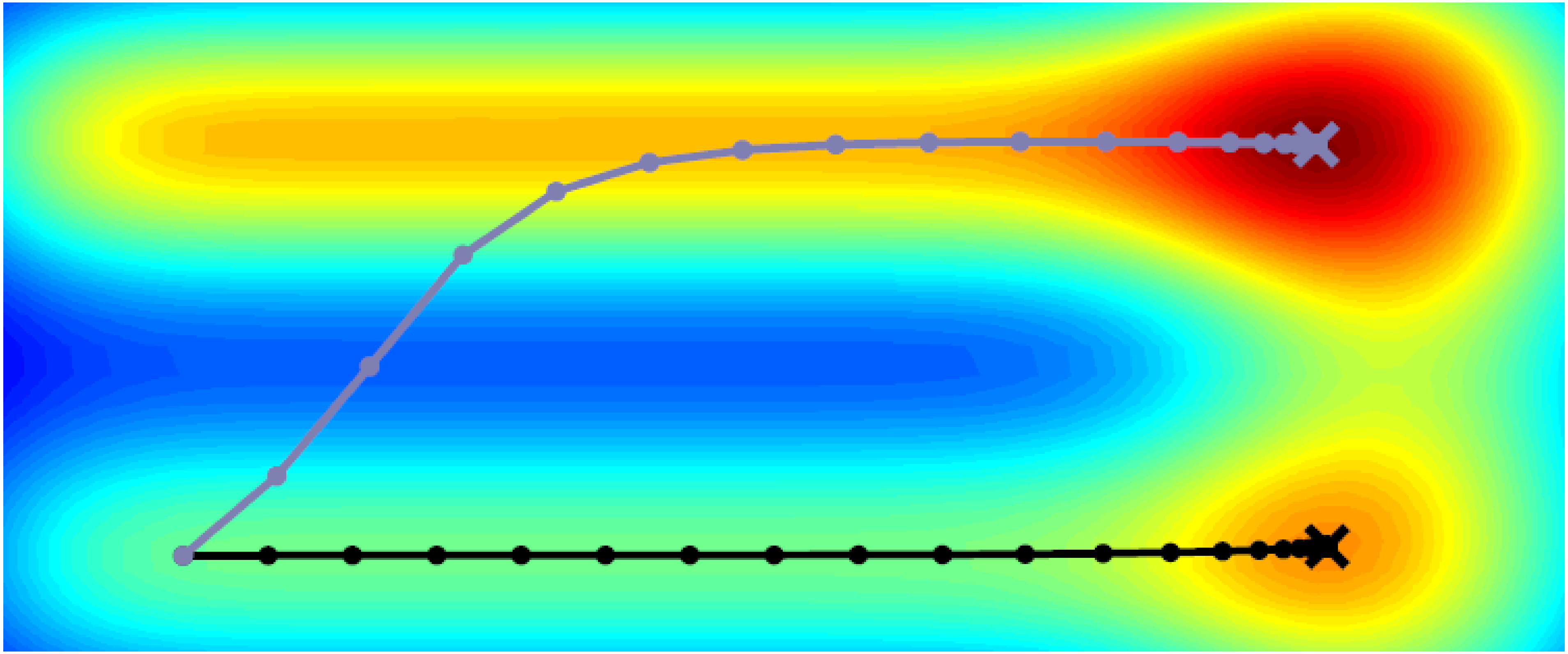
Arms showing planned positions


Peg Task



**Application:** Grabbing a needle after suture throw

# Paper 1: Continuous IOC with Locally Optimal Examples



S. Levine and V. Koltun. Continuous inverse optimal control with locally optimal examples. In Proceedings of the 29th International Conference on Machine Learning, ICML 2012, volume 1, pages 41 – 48, 2012.

# Inverse Optimal Control

For all future states reached

$$P(u \mid x_0) \propto \frac{1}{Z} \sum_t e^{r(x_{t,} u_t)}$$

The probability of choosing an action at a given state

Weighted feature responses at that state

# Inverse Optimal Control

$$P(u \mid x_0) \propto \frac{1}{Z} \sum_t e^{r(x_t, u_t)}$$

Partition function; extremely expensive to compute!

# Rewriting the Equation

Continuous version of
normalization term

$$P(u \mid x_0) = e^{r(u)} \left( \int_t e^{r(\hat{u})} du \right)^{-1}$$

Reward along path $(x_0, u)$

Reward along alternate
paths

# Second Order Taylor Expansion of Reward Function

$$r(\hat{u}) \approx r(u) + (\hat{u} - u)^T \frac{\delta r}{\delta u} + \frac{1}{2} (\hat{u} - u)^T \frac{\delta^2 r}{\delta u^2} (\hat{u} - u)$$

Gradient $g$

Hessian $H$

# Rewriting the Equation

$$r(\hat{u}) \approx r(u) + (\hat{u} - u)^T \frac{\delta r}{\delta u} + \frac{1}{2}(\hat{u} - u)^T \frac{\delta^2 r}{\delta u^2} (\hat{u} - u)$$

$$P(u \mid x_0) = \frac{e^{r(u)}}{\int_t e^{r(u) + (\hat{u}-u)^T g + \frac{1}{2}(\hat{u}-u)^T H (\hat{u}-u)} du}$$

Normalization term

Taylor expansion of the reward along alternate paths

# Gaussian Approximation

$$P(u \mid x_0) = \frac{e^{r(u)}}{\int_t e^{r(u)+(\hat{u}-u)^T g+\frac{1}{2}(\hat{u}-u)^T H\ (\hat{u}-u)}\ du}$$

$$= e^{\frac{1}{2}g^T H^{-1} g} + |-H|^{\frac{1}{2}}(2\pi)^{-\frac{n}{2}}$$

Dimensionality of $u$

$$\boxed{\frac{1}{2}g^T H^{-1} g + \frac{1}{2}\log|-H| - \frac{n}{2}\log 2\pi}$$

Log Likelihood

# Gaussian Kernel

$$\begin{cases} \log P(u \mid x_0) = \frac{1}{2} g^T H^{-1} g + \frac{1}{2} \log|-H| - \frac{n}{2} \log 2\pi \\ \log P(y, \lambda, \beta \mid F) = -\frac{1}{2} y^T K^{-1} y - \frac{1}{2} \log|K| + \log P(\lambda, \beta \mid F) \end{cases}$$

Gaussian kernel covariance

Gaussian kernel weights

Set of inducing feature points

**We can use either a linear or nonlinear kernel; the authors examine a Gaussian kernel.**

# Gaussian Kernel

$$\left\{\begin{aligned} &\log P(u \mid x_0) = \frac{1}{2} g^T H^{-1} g + \frac{1}{2} \log|-H| - \frac{n}{2} \log 2\pi \\ &\log P(y, \lambda, \beta \mid F) = -\frac{1}{2} y^T K^{-1} y - \frac{1}{2} \log|K| + \log P(\lambda, \beta \mid F) \end{aligned}\right.$$

Defined such that $K_{i,j} = k(f^i, f^j, \lambda, \beta)$

$$k(f^i, f^j, \lambda, \beta) = \beta \exp\left( -\frac{1}{2} \sum_k \lambda_k \left[ (f_k^i - f_k^j)^2 + 1_{i \neq j} \sigma^2 \right] \right)$$

# Gaussian Kernel

Hyperparameter log likelihood:

$$\log P(\lambda, \beta|\mathbf{F}) = -\frac{1}{2}\mathrm{tr}\left(\mathbf{K}^{-2}\right) - \sum_k \log\left(\lambda_k + 1\right)$$

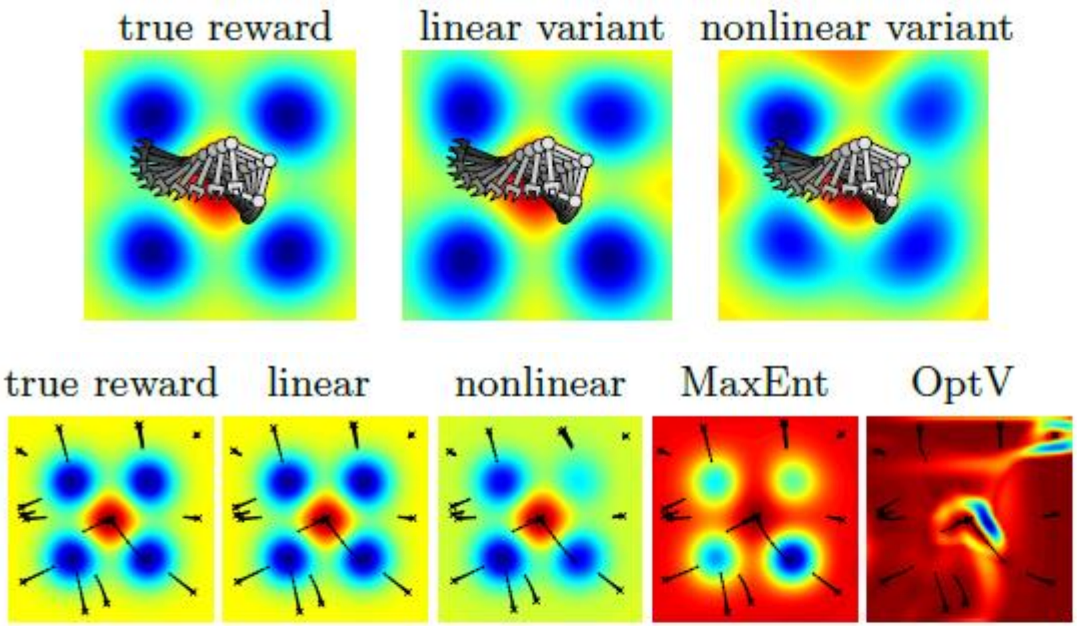
Reward at a given feature point:

$$r(\mathbf{x}_t, \mathbf{u}_t) = \mathbf{k}_t \alpha + \theta^{\mathrm{T}} \mathbf{f}_\ell(\mathbf{x}_t, \mathbf{u}_t)$$

$$\alpha = \mathbf{K}^{-1}\mathbf{y}$$

S. Levine and V. Koltun. Continuous inverse optimal control with locally optimal examples. In Proceedings of the 29th International Conference on Machine Learning, ICML 2012, volume 1, pages 41 – 48, 2012.

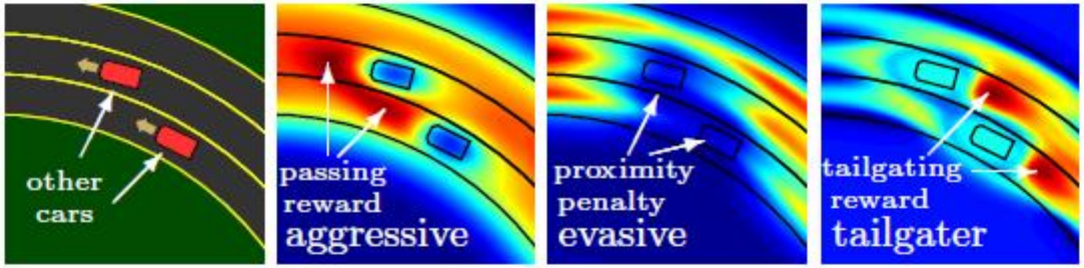
# Experiment: Multi-Link Arm




- Robot arm/planar navigation demonstrations computed according to a Gaussian reward function with four peaks
- Algorithm was best able to recover this reward function

S. Levine and V. Koltun. Continuous inverse optimal control with locally optimal examples. In Proceedings of the 29th International Conference on Machine Learning, ICML 2012, volume 1, pages 41 – 48, 2012.

# Experiment: Highway Driving

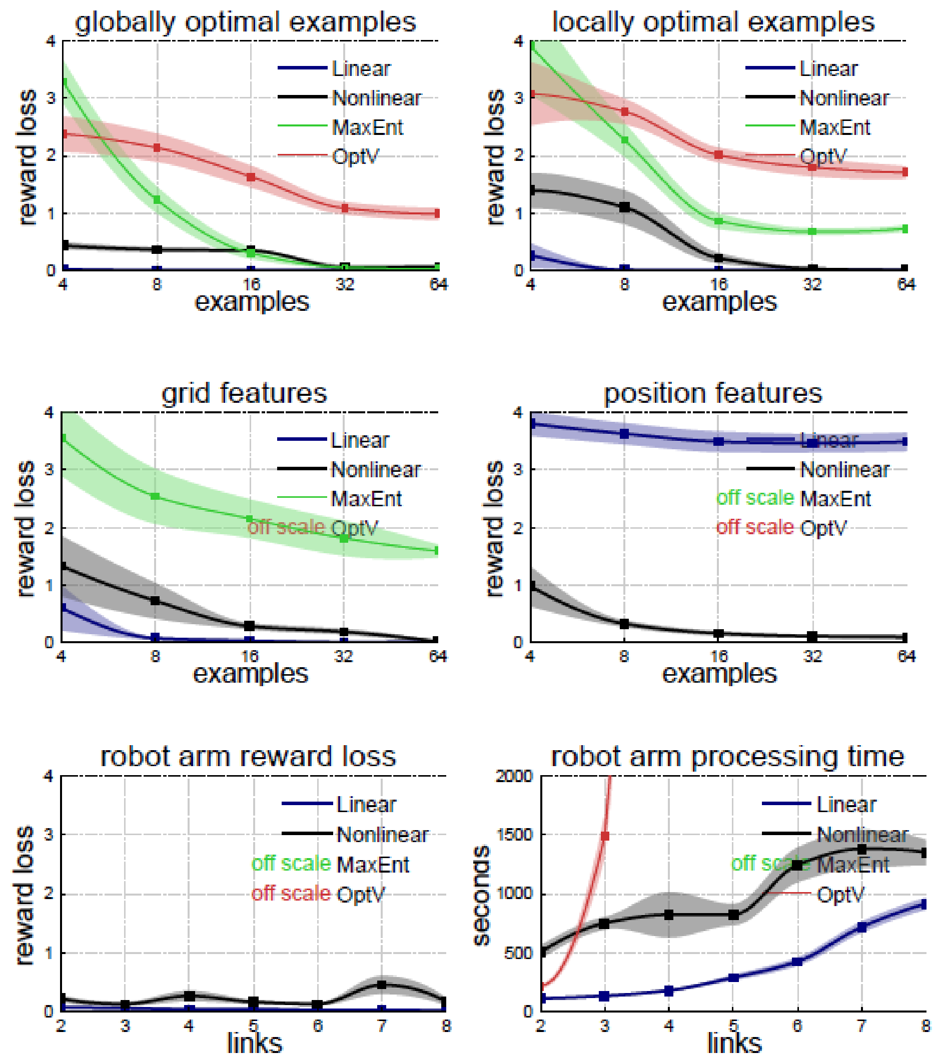



- Able to mimic different driving styles very effectively:
  - Tested with aggressive driving, evasive driving, or tailgating other cars
- Changed lanes to avoid other cars

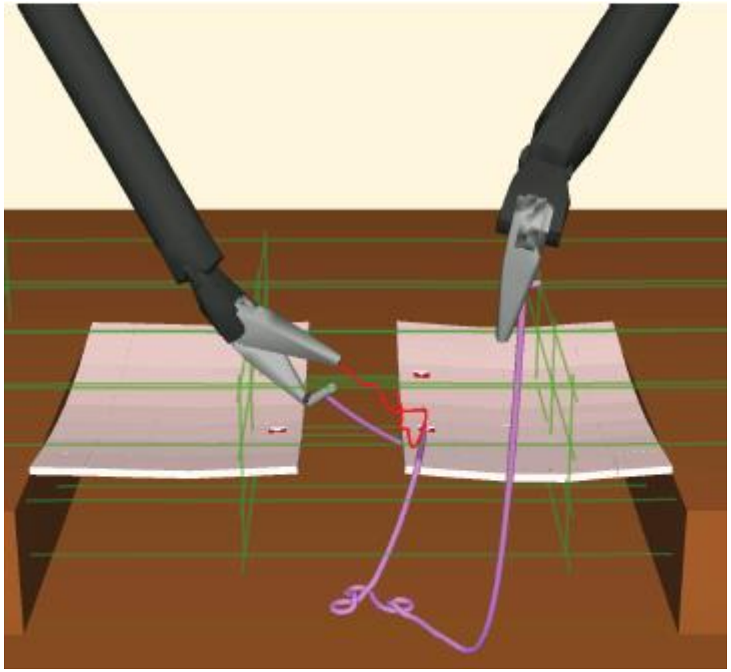
S. Levine and V. Koltun. Continuous inverse optimal control with locally optimal examples. In Proceedings of the 29th International Conference on Machine Learning, ICML 2012, volume 1, pages 41 – 48, 2012.

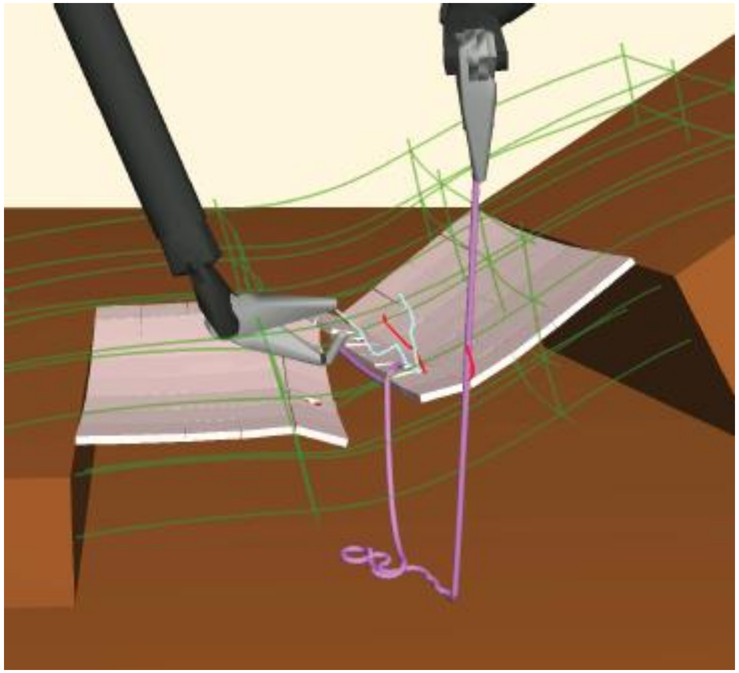
# Results

- Can be applied to locally optimal data
- Can be applied to limited features (ex: just position data, in the arm task)
- Comparatively efficient processing



# Paper 2: Trajectory Transfer Through Non-Rigid Registration

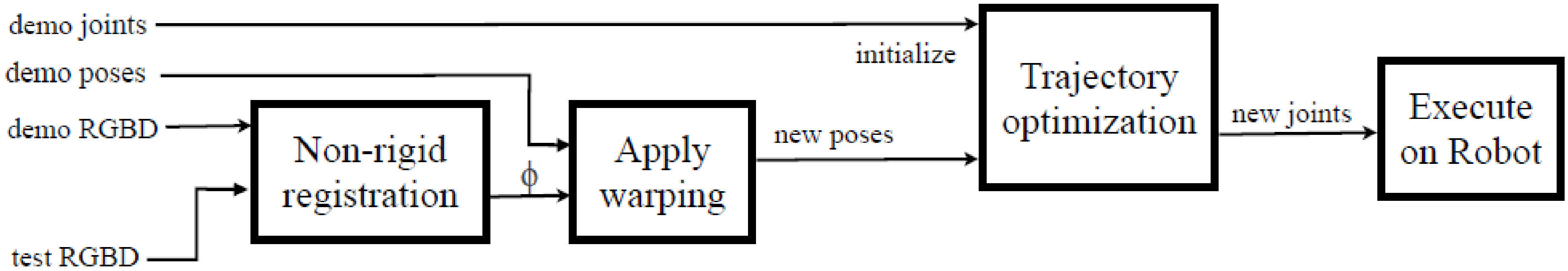




**Goal:** Collect demonstration of a task and apply it to a new world through a non-rigid registration followed by a warping.

John Schulman, Ankush Gupta, Sibi Venkatesan, Mallory Tayson-Frederick, and Pieter Abbeel. A case study of trajectory transfer through non-rigid registration for a simplied suturing scenario. In Intelligent Robots and Systems (IROS), 2013 IEEE/RSJ International Conference on, pages 4111{4117. IEEE, 2013.

# The Plan

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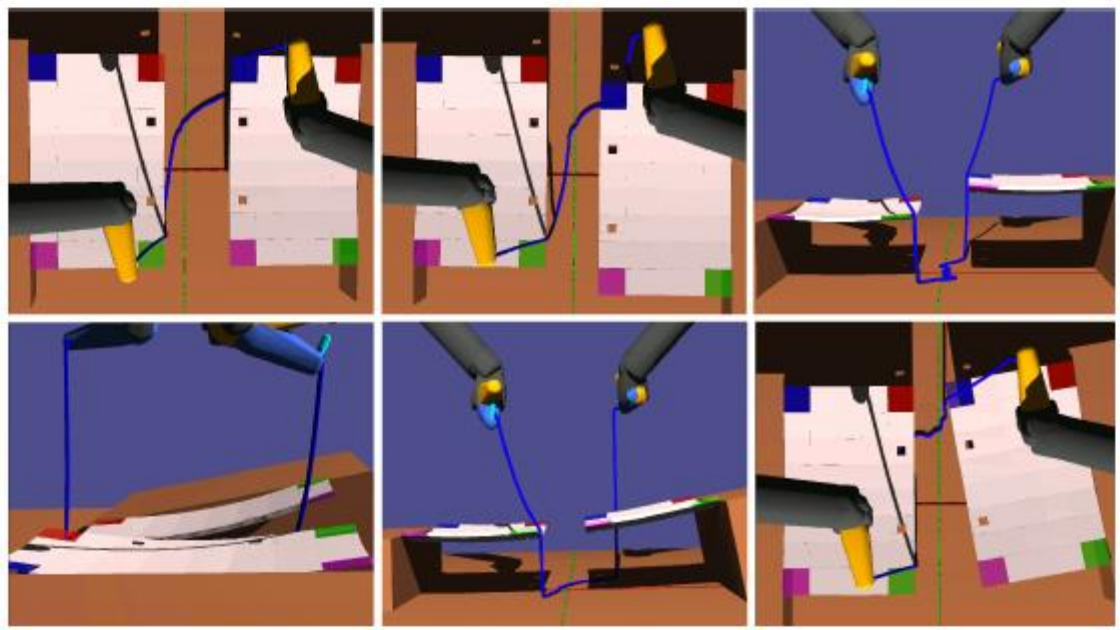
# The Plan

1. Find a transformation from the demonstration to the test scene.
    - Used Thin Plate Spline Robust Point Matching
2. Apply transformation to the demonstrated trajectory
3. Convert end-effector trajectory to a joint trajectory
4. Execute on the real robot

# Raven Simulation Results



- Applied different x,y,z translations and rotations to a second suture pad
- 64 possible combinations, with 10 possible scalings: 640 trials

John Schulman, Ankush Gupta, Sibi Venkatesan, Mallory Tayson-Frederick, and Pieter Abbeel. A case study of trajectory transfer through non-rigid registration for a simplied suturing scenario. In Intelligent Robots and Systems (IROS), 2013 IEEE/RSJ International Conference on, pages 4111{4117. IEEE, 2013.

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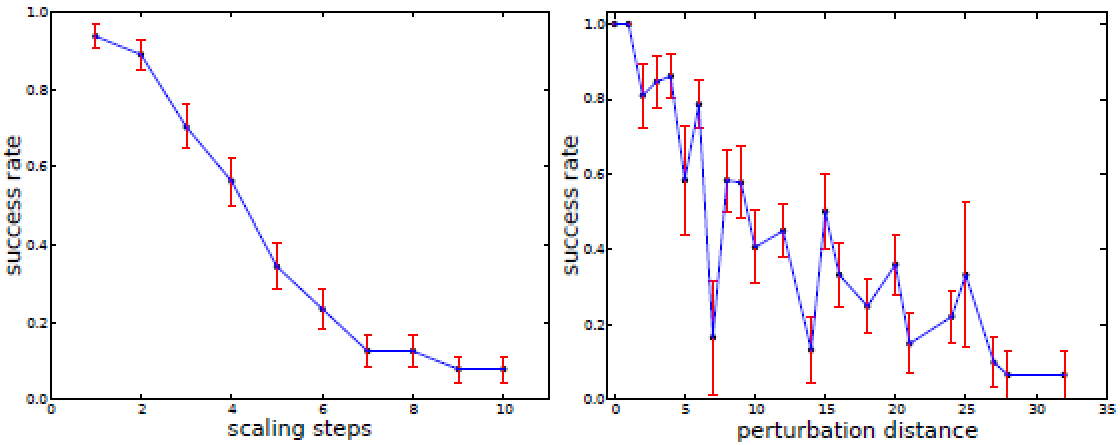


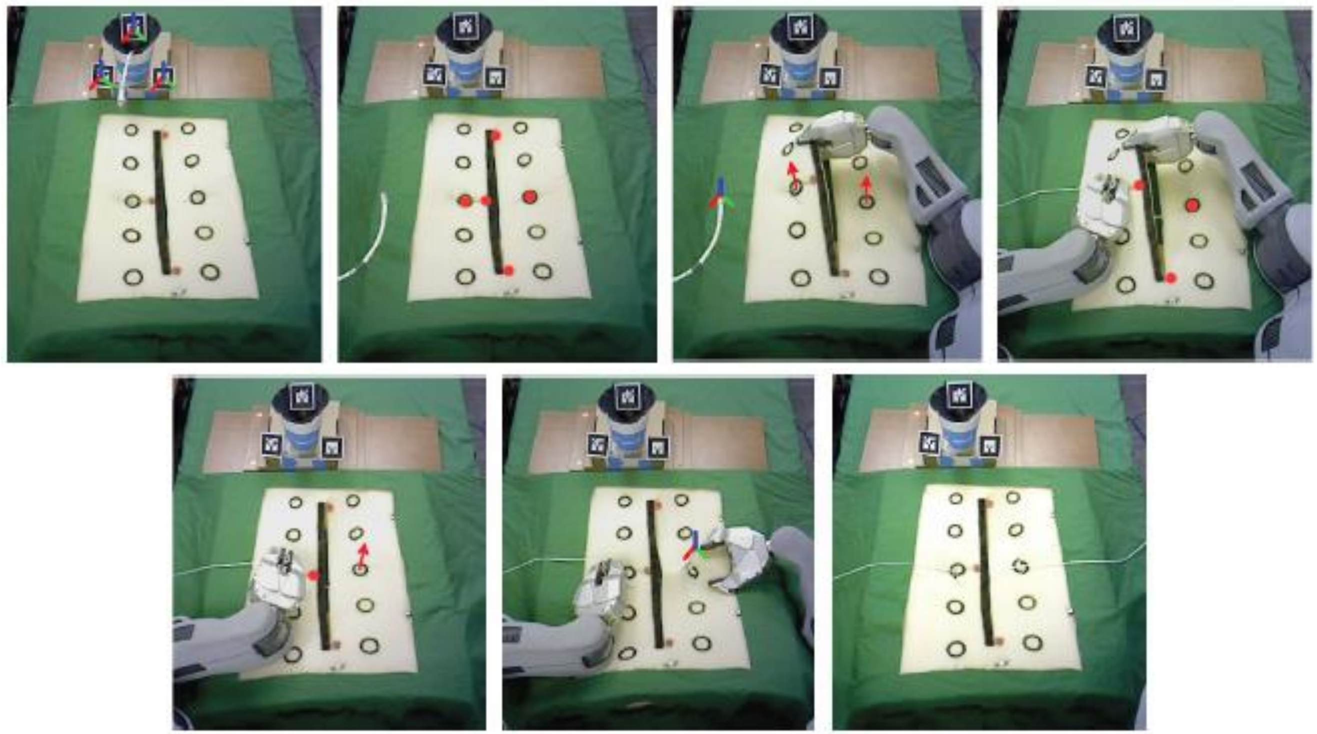

- Lower success rate with more scaling
- Common problems:
  - Grasping suture thread
  - Passing needle through holes
  - Suture moved during trial

John Schulman, Ankush Gupta, Sibi Venkatesan, Mallory Tayson-Frederick, and Pieter Abbeel. A case study of trajectory transfer through non-rigid registration for a simplied suturing scenario. In Intelligent Robots and Systems (IROS), 2013 IEEE/RSJ International Conference on, pages 4111{4117. IEEE, 2013.

# Real World Trial: PR2

Conor McGann, Eric Berger, Jonathan Bohren, Sachin Chitta, Brian Gerkey, Stuart Glaser, Bhaskara Marthi, Wim Meeussen, Tony Pratkanis, Eitan Marder-Eppstein, et al. Model-based, hierarchical control of a mobile manipulation platform. In 4th workshop on planning and plan execution for real world systems, ICAPS, 2009.

# PR2 Suturing Results



- Task: pierce and re-grasp needle
- Human identified suture points; procedure was not entirely automatic

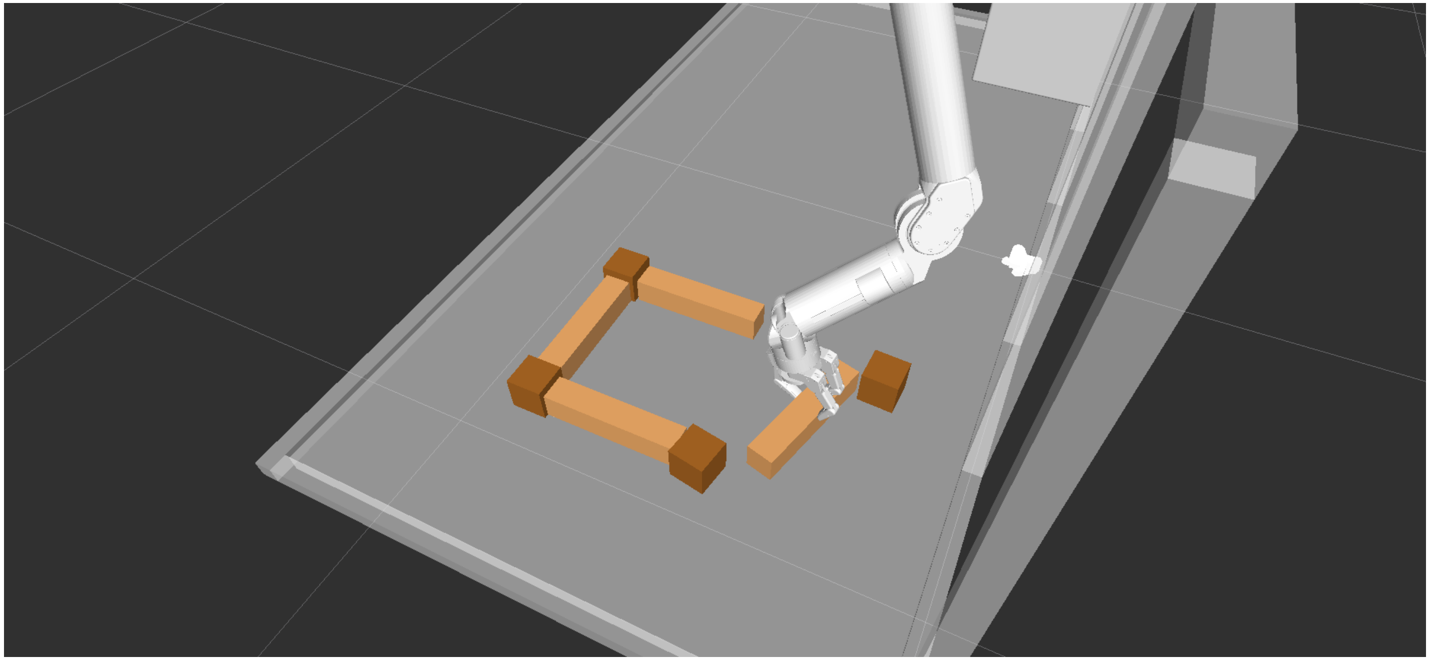
John Schulman, Ankush Gupta, Sibi Venkatesan, Mallory Tayson-Frederick, and Pieter Abbeel. A case study of trajectory transfer through non-rigid registration for a simplied suturing scenario. In Intelligent Robots and Systems (IROS), 2013 IEEE/RSJ International Conference on, pages 4111{4117. IEEE, 2013.

# PR2 Suturing Results

- 87% overall success rate
- 100% success rate with low pertrubations
- Successful even in the case of deformations on the x or axis

| Perturbation | Success Rate |
|---|---|
| 10° $x$ rotation | 2/2 |
| 15° $x$ rotation | 2/2 |
| -10° $x$ rotation | 2/2 |
| -15° $x$ rotation | 1/2 |
| 10° $y$ rotation | 2/2 |
| 15° $y$ rotation | 2/2 |
| -10° $y$ rotation | 2/2 |
| -15° $y$ rotation | 2/2 |
| 10° $z$ rotation | 2/2 |
| 15° $z$ rotation | 0/2 |
| -10° $z$ rotation | 2/2 |
| -15° $z$ rotation | 2/2 |
| Bend $x$-axis | 2/2 |
| Bend $y$-axis | 2/2 |
| Diagonal holes | 1/2 |

# Relevance



- Both methods may be useful for learning from demonstration
- The second method is easier to implement, and may be more practical as a starting point

Questions?